COMPUTATIONAL INTELLIGENCE IN COMPUTER AIDED PROCESS PLANNING – A REVIEW

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S u m m a r y

This paper first provides a general introduction to Computer Aided Process Planning (CAPP). In second section, a brief review of Computational Intelligence (CI) applications in machining process planning and related methods and problems will be presented. The overall applications can be classified as knowledge representation, features extraction, part classification for group technology, machining volume decomposition, tool path generation, machining condition optimization, operation sequencing, machine, setup and tool selection, modeling the EDM process, and others. It presents current state and perspectives on computational intelligence in CAPP.

Keywords: computational intelligence, CAPP, knowledge engineering

Inteligencja komputerowa w komputerowo wspomaganym projektowaniu procesów

S t r e s z c z e n i e

W pracy omówiono obszary zastosowania metod sztucznej inteligencji w komputerowo wspoma-ganym projektowaniu procesów wytwarzania w budowie maszyn. Podjęto próbę klasyfikacji tych obszarów. Przedstawiono najważniejsze zdaniem autora osiągnięcia inteligencji komputerowej w budowie efektywnych systemów CAPP. Określono tendencje i zadania w dalszym rozwoju systemów CAPP i rolę inteligencji komputerowej, jako narzędzia inżynierii wiedzy, w ich realizacji.

Słowa kluczowe: inteligencja komputerowa (obliczeniowa), CAPP, inżynieria wiedzy

1. Introduction

Currently, advances in information and communication technology have forced industrial activities to use computers in each phase of the manufacturing process. Computer Aided Process Planning is one of the most important advances in the area of manufacturing engineering. Process planning are ordered sequences of task able to transform raw material into a final part economically and competitively. The major process planning activities are interpretation

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of product design data, selection of machining processes, determination of datum surfaces and fixtures, sequencing the operation, determination of production tolerances, determination of the cutting parameters, estimation of production times and generation NC data. Planning (CAPP) has a strong impact on manufacturability, product quality and production cost.

Manual process planning is very time-consuming and the result depends on the person doing the planning. Computerized process planning systems can help reduce the time from design to manufacturing, reduce product cost, increase the quality of the final product owing to the elimination of human error, and increase plan consistency and efficiency. Computer-aided process planning is a bridge between design and manufacturing in a computer-integrated manufacturing (CIM) environment. The interface between CAD, CAM and CAPP area (Fig. 1) is still a topic of many research activities. New approaches tend to integrate CAD, CAPP and CAM system, by using feature-based technology. Computer-aided process planning initially evolved as „variant" CAPP, based on a Group Technology. Variant approach relies on standard plans developed from previously manufactured similar parts. In – the next stage of evolution – generative CAPP, process planning decision rules are built into the system (Fig. 2). Simultaneously, some computer aided process planning system developers have attempted to combine some features of both approaches forming another category what is called semi-generative (or hybrid) CAPP. The current research efforts on CAPP systems focus on both variant and generative but also on hybrid systems, which is considered a good direction for current industrial applications. The system combines variant and generative approach and are capable of generating plans that are suitable for parts that either are similar to existing parts or new. Recently, a new trend toward integration is to utilize adaptive, dynamic and distribution process planning implies that production instructions for machining a part are generated dynamically and adaptively in accordance with changeable shop floor status. In other words, process plan information is generated in real-time in the shop floor based on current information of shop states.

Different researchers adopted different advanced techniques and approaches such as feature or solid model based design, object oriented programming, manufacturing databases, and used advanced computing methods including expert system and artificial intelligence (AI). The decision logic in process planning may be based on decision trees, decision tables, heuristic methods, rule based decision trees, constraint-based methods, hard coded algorithms, and problem oriented languages. Because process planning is a NP-hard problem, some global search techniques must be applied.

Artificial intelligence is an old dream and a fairly young discipline, which has developed since the late 1950 s as an interdisciplinary branch of computer

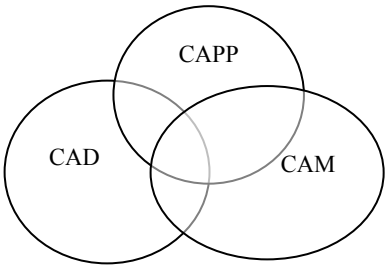

Fig. 1. The areas catenation among CAD, CAM and CAPP systems

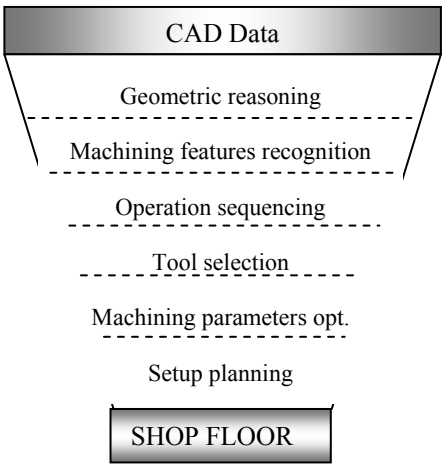

Fig. 2. The general architecture of the CAPP system

and cognitive sciences aiming at computational models of human cognition. AI is not intended to replace human intelligence. It is rather a marketing name for new programming methods to create reasoning systems [1]. The modern definition of AI is "the study and design of intelligent agents" where an intelligent agent is a system that perceives its environment and takes actions which maximizes its chances of success. For the user intelligent agent is a black box [2]. Computational intelligence (CI) is a successor of artificial intelligence. CI is an alternative to GOFAI (Good Old-Fashioned Artificial Intelligence). GOFAI developed as the project of empirical research, implements a weak model of semantic networks. CI rather relies on heuristic algorithms such as fuzzy systems, artificial neural networks (ANN's), evolutionary computation, artificial immune systems etc. Computational intelligence combines elements of learning, adaptation, evolution and fuzzy logic (rough sets) to create programs that are, in some sense, intelligent. The successful use of CI in many science and

engineering areas reveals that CI techniques are applicable to process planning. CAPP systems have greatly benefited from CI methods due to their knowledge processing and logic programming capabilities. Fuzzy values are used to describe possible values of the parameters which are represented by the linguistic variables. In the process planning field ANN's have been applied successfully to function approximation, pattern recognition, sequential decision making, filtering, clustering and self-organization of knowledge. Genetic algorithms (GA) have been successfully applied to various optimization problems. The hybridization approaches, such as genetic-fuzzy, fuzzy-neural (Fig. 3), etc, are aimed not only at exploiting the strong capabilities of the various tools, but also at solving manufacturing problems that are not amenable for modeling using traditional methods. The logical fuzzy inference is used as the computational method, where the system is developed in logical programming languages such as Prolog or other AI programming languages.

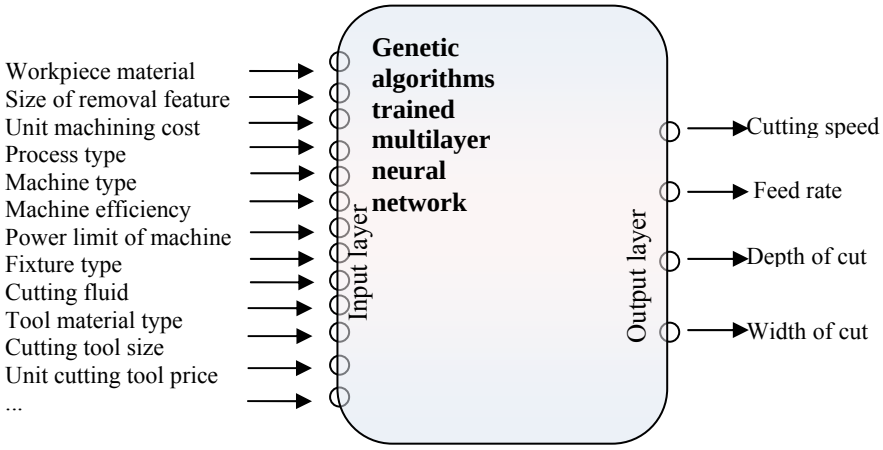

Fig. 3. General structure of the hybrid (ANN/GA) system

The previous state-of-the-art for application AI (or CI) in automated process planning reports Alting and Zhang [3], Huang [4], Kiritsis [5], Lueng [6], Knosala [7], Wang et al [8], Kolli [9], Ahmad et al [10], and Li et al [11].

2. A review of CI methods in CAPP systems

Many researches and developers of CAPP systems try to incorporate some intelligence in their applications in order to built in some manufacturing

knowledge. Most researches indicated features to be the primary method for part description.

Recognition of geometric features is important for automatic evaluation of part designs and development of process plans. Feature recognition is defined [12] as a search process in which a pattern of the entities in the geometric model is compared with the generic definitions of previously defined features. In the feature recognition process the values of the feature parameters and feature interactions are determined. Recognition of features from solids models has proceeded along two general fronts: recognition from boundary models and recognition from volume-based models.

Automated recognition and classification of features from a boundary-representation solid model was first attempted in the mid-1970's. A number of approaches have appeared in automatic feature recognition using boundary representation. Some of these are syntactic pattern recognition, logical inference (expert system approach), graph-theoretic, declarative feature description language, ANN's. Prabhakar [13], in the first attempt known to use ANN techniques for solid model feature recognition, developed a system called FRENET (Feature Recognizer and Extractor based on Neural net Evaluation Technique). Marquez et al [14] a tree-layer ANN system is created and trained using backpropagation supervised learning to recognize nine of the most important features related to this manufacturing process. Öztürk and Öztürk [15] implement a multi layer perceptron (MLP) with two hidden layers to recognize machining features. Further ANN's application for feature recognition can be found in [16]. Stryczek [17] proposed four different approaches to feature clustering, classification and part family formation. The use of traditional shape coefficients (Danielsson, Haralick, and others) has not given satisfying results. The use of ANN has proved very effective on the learning stage. However, this method generated a big percentage of incorrect classification in the case of new features without training set. The clustering method of object grouping based on the nearest neighbour algorithm, which makes use of the data from the raster image is natural intuitive, has very good results on the grouping stage as well as in the process of new forms classification. It succeeds in finding the most similar machining form features. In the last method, based on generating fuzzy synthetic representatives, the only disadvantage is the fact that the proposed cellular automata based procedure of fuzzyfication is very time consuming. In [18] proposed unconventional approach, based on cellular automata use to machining volume decomposition. Based on raster graphics image of raw material and workpieces, the machining form features are extracted. The effective utilization of this method is intimately connected to the availability of multiprocessors computers and/or parallel computing. Moon and Chi [19] used a ANN model to solve the part family formation problem. Authors combined ANN technique with the flexibility of the similarity coefficient method.

Feature completion, and setup planning are the most important part of a CAPP. The setup planning in manufacturing consists mainly of three steps, namely, setup generation, operation sequence, and setup sequence. Especially in operation sequencing and scheduling tasks such hybrid systems may play an important role. Process sequencing is a process of analyzing the internal relations and affections of many factors in machining. The problem of operation sequencing is affected by number of parameters such as tool compatibility, feature accessibility, feature orientation, features interaction, dimensional tolerance, geometric tolerance, location tolerance, surface finish and safety. Process sequencing is difficult to by solved exactly with mathematical expression. The optimization of process sequences is a very complex and difficult task. It there is similarity between process route optimization and the Travelling Salesman Problem (TSP).

Ssemakula et al [20] discussed how AI techniques can be used in the optimization of process sequences. Based on the nature of the problems involved in process sequencing, they analyzed the computational complexity of process sequence optimization, and describe some algorithms for optimization of process sequences based on heuristic search techniques. Knapp and Wang [21] demonstrated the ability of ANN in the process selection and within feature process sequencing. Two co-operating ANN were used: the first one takes in as input the attributes of a feature and proposes a set of machining alternatives, another selects exactly one of the alternatives. Ahmad and Haque [22] and Deb et al [23] demonstrated the potential, of the back-propagation ANN approach to process selection for cylindrical surface machining. The three layers are organized into feed forward system, no feedback connections to the previous layer. Ming and Mak [24] used Kohonen self-organizing ANN to generate setups in terms of the constraints of fixture/jigs, approach direction, feature precedence relationships, and tolerance realationships. The operation sequence problem and the setup sequence problem are mapped onto the TSP, and are solved by Hopfield ANN's. Shan and al [25] combined an expert system and a ANN for a two stage machining operation sequencing. They used the modified Hopfield ANN to minimize the production cost. A simulated annealing scheme is used to determine the probability of a neuron state change to keep away from being trapped into a local minimum. Zhang et al [26] based on a analyzing of various constraints in process sequencing, the GA's adopted in process route sequencing. In this method the natural number is adopted in coding strategy, and the operators of selection, crossover and mutation are executed on the population repeatedly to search the optimal or near-optimal process route in the global feasible space. Yip_Hoi and Dutta [27] presents a GA for generating plans for machining a Mill/Turn part that satisfies both the constraints of the geometry of the part and the restrictions due to the configuration of the machine-tool environment, while at the same time minimizing the part machine time. Operation sequencing in nonlinear process planning is the problem of

simultaneous selecting and sequencing operations required to produce a part while satisfying the precedence relations among operations. Lee et al [28] simulated annealing and tabu search algorithms are suggested after decomposing the problem into two sub-problems: operation selection and operation sequencing. Pandey et al [29] the simulated annealing based algorithm employed to datum selection, determination the near-optimal operation sequence, and to grouping features into setup by maximizing operation sequencing rating index. Dereli and Filitz [30] presented an optimization system developed for determining optimal sequence of machining operations based on either minimum tool change and/or minimum tool travelling distance and/or safety (based on either geometric constraints or strength). GA based optimization system gives best response to the safety criterion. Krishna and Rao [31] presented an application of a newly developed mataheuristic called the ant colony algorithm as a global search technique for the quick identification of the optimal operations sequence by considering various feasibility constraints. It is possible that they may by alternative sequences correspond to the same lowest total cost. Szadkowski [32] the heuristic rules have been formulated for structural problem of the process ordering and computer aided search for optimal solution. For the process performance maximization and the number of the machining station minimization two groups of methods have been used: manufacturing lines balancing algorithms and algorithms derived directly from K-graph. Sormaz and Khoshnevis [33] the space search algorithm used for process sequencing and process clustering. Process clustering is applied at two levels: clustering for the same tool axis direction (on the same machine) and clustering on the machine level for a set of cluster from the previous level. The clustering procedure serves as a heuristic to reduce a state space for sequencing. Process sequencing is a result of a state space search from a initial state (raw stock) in which no feature is machined to the goal state, the finished part. Sormaz [34], discussed an application of a hybrid of space search, Dijkstra's, and k-path algorithm on the network for generation of process plan. This methodology dramatically reduces the search space because it does not explore all the possible state space. An improved space search algorithm, which simultaneously generated process sequence and optimizes the process plan is described. Incremental refers to the fact that the manufacturing plan is updated after each design process.

Setup planning is the key to CAD/CAM integration because it takes product design and manufacturing requirement information from a CAD model and provides information to CAM for NC programming, datum selection and fixture design. Huang and Xu [35] presented a summary of the literature on setup planning. Ong and Nee [36] reported a fuzzy-based set-up planning system. The concept is facilitated by the use of fuzzy sets and fuzzy relations in the representation of various feature relations. Stryczek [37] used fuzzy set theory to features interaction modeling, and setup sequencing.

The optimization problem for sequence of operations is similar to the optimization problem for index position of cutting tools to be used on the tool magazines of CNC machine tools. Dereli and Filitz [30] a GA based optimization system has been developed for allocating the optimal index positions on the tool magazine to the specified cutting tools. Selection of cutting tools using an expert system presented Arezoo et al [38].

Tool path generating is regarded as a TSP problem for a tool to go through all the point of the given feature so that the ANN method, especially Kohonen self-organization feature map ANN [39]. Balic and al [40] shows how useful the use of ANN's can be to free surface milling programming. They set up the surface quality as primary technological aim. When the changing technological aim, then the learning model should be reorganized according to the new technological goal.

It is not possible to run the CNC machine tools effectively without using optimized machining parameters. Optimal machining conditions are the key to economical machining operations. The machining parameters, as cutting speed, feed rate applicable for selected cutting tools, depth of cut for each pass, number of passes for each operation, and width of cut, plays an important role in efficient utilization of machine tools and significantly influence the overall manufacturing cost. Determination of the optimal cutting parameters is considered as an indispensable stage in process planning. The optimal cutting parameters are not easy to determine because there exist multivariate relationships among cutting parameters and operating factors. To solve the optimization problem for cutting parameters many methods have been used, include the use nomograms, graphical methods, linear programming, geometric programming, dynamic programming techniques, numerical search and CI techniques [41]. Most of the works using CI have been carried in the last fifteen years. Wong and Hamouda [42] used a feed-forward ANN to predict optimum machining parameters under different machining conditions. The back-propagation algorithm was used to optimize the network component representation. Khan et al [43] some benchmark machining models are evaluated for optimal machining conditions. In this research, used GA's and simulated annealing as optimization methods for solving the benchmark models. The results are compared with each other as well as with previously published results which used gradient based methods, such as: Sequential Unconstrained Minimization Technique, Box's Complex Search, Sequential Search Technique, Generalized Reduced Gradient, etc. Cus and Balic [44] a combination of ANN and GA was also used for determining cutting parameters in machining operation. Dereli and Filitz [30] for the optimization of multi-pass milling operations, a GA based system called Cutting Parameters Optimization System (CPOS) developed. CPOS has a multi-pass optimization strategy incorporating several technological constraints such as power, surface finish, speed, feed limitations, etc. Alam et al [45] presented system IMOLD_CAPP, where

selection of machine tools, cutting tools, and cutting conditions for different processes in the plan template are optimized by a method based on GA's. The objective function of optimization is to minimize overall processing time. The performance of the optimization is compared with an algorithm based on simulated annealing. Joo et al [46] presented ANN to estimate cutting force and tool life coefficients determination. Hashmi et al [47] have developed a fuzzy reasoning method for selection of machining speed for a depth of cut, material hardness. The application of fuzzy reasoning methods offers rule based knowledge representation similar to the expert systems approach. Selection conditions of machining operations using an expert system presented Arezoo et al [38].

To make a given feature to its final size, different sets of tools with different cutting speeds may be used which directly influences tooling and machining costs. The cost associated with each operation is both sequence-dependent and position-dependent. Kolahan and Liang [48] reports a tabu-search approach to minimize the total processing cost for hole-making operations. This problem has a structure similar to the TSP in which each node (operation) in a tour (sequence of all operations) must be visited only once. The estimation of future production cost is a key factor in determining of a new product's development and product redesigning process. The cost per unit is the sum of different resources such as of materials, energy, machinery, tools and plants. The quantification of the use of each resource is extremely difficult. Cavalieri [49] proposed an ANN technique for the estimation of the unitary manufacturing costs of a new type of brake disks. The results seem to confirm the validity of the ANN theory in this application field. Shebad and Abdalla [50] proposed to overcome uncertainty in the knowledge of cost model, a fuzzy logic model to generated reliable estimation of cost.

Wang et al [51] discusses the development and application of hybrid ANN and GA's methodology to modeling and optimization of electro-discharge machining. The first phase of hybridization involves the establishment of the model using multilayer feedforward ANN architecture. The input variables are duration of each spark, pause time between two sparks, maximum current during spark, voltage between electrode and work piece, servo sensitivity to changes in spark gap. The performance parameters are ratio of volume of material removed from the work piece to time required for removal and measure of surface quality on machined part. The GA's finds the optimum values of the weights that minimize the error between the measured and the evaluated performance parameters.

Production systems are complex in nature and difficult to optimize using conventional techniques. Production scheduling is the allocation of resources over time to perform a collection of task. Of all kinds of production scheduling problems, the job shop scheduling is one of the most complicated problems. Fonseca and Navaresse [52] developed a feed-forward multilayered ANN

through the back error propagation learning algorithm to provide a versatile job shop scheduling analysis framework. In the conventional approach the scheduling function is isolated from process planning. Traditional CAPP systems aim to obtain optimal or near-optimal machining processes from a single job shop. However, in a distributed manufacturing environment, there are other available factories capable of performing a task, and it is possible that one of them may provide a more efficient and better process plan. Real manufacturing system are affected by a lot of disturbance like breakdowns, dynamic bottlenecks, unforeseen changes of job priority, etc. Therefore, Li et all [11] the GA proposed to developing a CAPP system, which can produce process plans in a distributed manufacturing environment. Lee and Kim [53] proposed a new approach to the integration of process planning and scheduling using simulation based GA's. The method uses the output of the scheduling module as the input of the fitness function of the GA. A simulation model is used to compute the performance measures and a GA is used to evaluate and select the best process plan combination. By applying the proposed methodology in the industry, the bottleneck problems of shop floor were much reduced and consequently the throughput of the parts was significantly increased. Palmer [54] a simulated annealing approach proposed to integrated production scheduling. Also Li and McMahon [55], a unified representation model and a simulated annealing-based approach have been developed to facilitate the integration and optimization process. In this approach, three strategies, including processing flexibility, operation sequencing flexibility and scheduling flexibility, have been used for exploring the search space to support the optimization process effectively. Joo et al [39] proposed a conceptual framework of the adaptive and dynamic process planning system that can rapidly and dynamically generated the needed process plan based on shop floor status. The dynamic planning models are constructed as ANN form, and then embedded into each process feature in the process plan. Chang and Chang [56] an integrated artificial intelligence system for dynamic computer-aided process planning (IAI-CAPP) system presented. IAI-CAPP system integrates fuzzy logic and ANN's to perform the dynamic recognition and adaptive-learning tasks of the workpieces and process plans. In addition, the technique of expert system is utilized. Also Zhang and Mallur [57] proposed a Fuzzy set theory for the selection of a feasible process plan based on the machine set-ups. The objectives of this system is to minimize the number of set-ups, minimize the number of processing steps, and improve the machining accuracy. Zhang and Huang [58], a fuzzy approach used to deal quantitatively with the imprecision of the process plan selection problem. Each process plan is evaluated and its contribution to shop-floor performance is calculated using fuzzy set theory.

Table 1. A review of CI applications in machining process design

	CI methods									
	Ant Colony	Cellular Automata	Fuzzy Logic (Rough Sets)	Genetic Algorithms	Intelligent Databases	Neural Networsks	Pattern Recognition	Tabu-Search	Simulated annealing	Khnowledge based approach
Knowledge representation			Y		Y	Y	Y			X
Process planning tasks										
Features extraction(recognition)		Y				Y	Y			Y
Part classification			Y			Y	Y			Y
Volume decomposition		Y	Y			Y	Y			Y
Tool path generation				Y		Y				
Machining parameters optimization			Y	Y	Y	Y	Y	Y	Y	Y
Machine tools selection				Y	Y	Y	Y		Y	Y
Operation sequencing	Y		Y	Y				Y	Y	Y
Set-ups planning			Y	Y	Y					Y
Tool specification					Y		Y	Y		Y
Tool magazines optimization				Y						
Production cost estimation			Y		Y	Y	Y	Y		Y
Modelling the EDM process			Y	Y		Y				
Production scheduling			Y	Y	Y	Y	Y		Y	Y
Manufacturing cell formation			Y	Y		Y				Y

Cell formation is a key issue in implementing cellular manufacturing and consist of decomposing the shop in distinct manufacturing cells, each one dedicated to the processing of a family of similar part types. Guerero [59] proposed a methodology for cell formation in which a self-organizing ANN is

used to compute weighted similarity coefficients and clusters parts. Venugopal and Narendran [60] formulated the machine-cell-formation problem as the objective function for GA's optimization to minimize the volume of inter-cell moves.

The following three papers apply hybrid approach of most recent technique of computational intelligence as the interface engine of the developed CAPP system. Amaitik and Kiliç [61] presents an intelligent process planning system using features (ST-FeatCAPP) for prismatic parts. Rojek-Mikołajczak and Weiss [62, 63] presented intelligent database based on AI software package Sphinx and MS Access.

3. Conclusion

A CAPP system architecture which is built in terms of hierarchical layers would be desirable, since such systems are required to perform macro and micro level process planning.

The future CAPP systems should have modular structure, open architecture, graphical user interface, should be user friendly, easy to customize, easy to maintain, available with standard interfaces, have monitor the actual production and feed the changes in the status the shopfloor back to the system planner.

Computational intelligence has the largest impact on the recent advances in CAD/CAM integration, especially in effective integration of CAPP and CAM function (Table 1). The non-traditional methods, as GA's and Simulated Annealing, offer the maximum advantages when the problem is highly non-linear and non-convex. A major drawback of this methods is that finding high quality solutions may require large computational effort and make these methods not very attractive for real-time parameter optimization. The computational cost of GA's can be reduced by adopting an artificial selection mechanism in addition to the common natural and by using adaptive penalty approach. In another heuristic method tabu-search can considerably reduce the computational time. A unified hybrid intelligent approach which is the combination of a knowledge-based system and computational intelligence for modeling product design and its related machining processes is very promising for intelligent manufacturing.

It is not yet clear if an efficient process planning system needs to by totally automatic [5]. The rule is: if you know precisely the algorithm to solve your problem do not apply CI; or, if CI cannot help to solve your problem sufficiently, then develop a user interface. Computational Intelligence techniques would be utilized more extensively in developing future CAPP systems. The potential and the power of CI is very great. Experimental results show that the proposed, CI-based methods are bath effective and efficient with respect to the quality of solution and the solving speed. By applying the CI, the

CAPP system can generate optimal or near-optimal process plans based on the criterion chosen. With CI-based optimization systems, it would be possible to increase machining efficiency by the use optimal cutting parameters, sequence of operations, etc. It can be integrated into an intelligent manufacturing system for solving complex machining optimization problems. Most proposed CI methods are a search strategy ideally suited to parallel computing. However, more user friendly software for CI application with strong mathematical calculation capabilities is necessary.

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